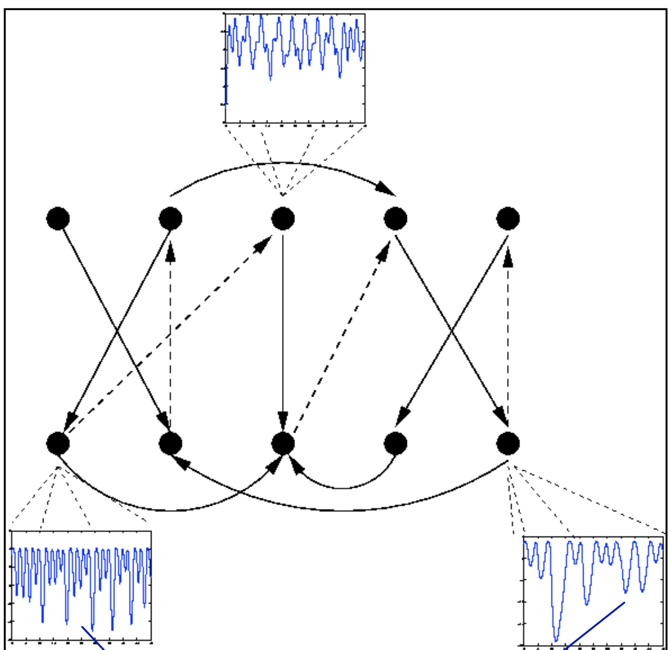
Prognostic Tools for Complex Dynamical Systems

Modeling systems as networks of coupled nonlinear dynamical systems allows the structure of the coupling between the systems to be used as a diagnostic tool. The structure reveals cause-and-effect relations, and changes in these relations may predict transitions to undesirable modes of operation. Diagnosis of incipient faults allows safer and more cost-effective operations.


time-series data from a given node

Systems are designed to operate in certain modes, and these modes correspond to certain couplings between the subsystems. However, unanticipated external impacts on the system, or system degradation, can cause the couplings to change. These changes in couplings can cause the system to switch to a different mode of operation, one that may be at reduced efficiency (e.g., solar panel based power systems have an undesirable mode where only about 30% of rated power is delivered) or may result in a catastrophic failure.

It is clear that being able to learn, on-line, the actual (rather than nominal) structure of the coupling between the subsystems would enable early diagnosis of transitions to undesirable operating regimes, and would increase the safety and reliability of the overall system.

The figure illustrates a set of dynamical systems (black circles) connected into a network. From time-series measurements of each system behavior (blue plots) , the structure of the network can be learned.

Background

Many systems actually consist of a number of sub-systems, coupled to one another. For example, a rocket engine consists of a number of tanks, turbo-pumps, reaction chambers etc, coupled together through pressurized feed lines and control systems. An electrical power distribution system consists of a number of sources and sinks, connected by switchgear. In each case, the combined system has modes of operation that are emergent, and cannot always be predicted easily from studies of the subsystem behavior. In particular, the specifics of the coupling between the subsystems has a large influence on the behavior of the combined system.

Research Overview

We have recently developed a new method for the statistical inference of dynamical networks representing a potentially complex structures of interconnected dynamical subsystems. Each node of a dynamical network represents a dynamical system with a well-identified topology (e.g. limit cycle or other nonlinear oscillator). The coupling between the nodes of the network corresponds to the coupling between the corresponding dynamical subsystems and can be visualized as the edges of the network - every edge connecting a pair of nodes corresponds to a set of coupling coefficients between the dynamical variables for those nodes.

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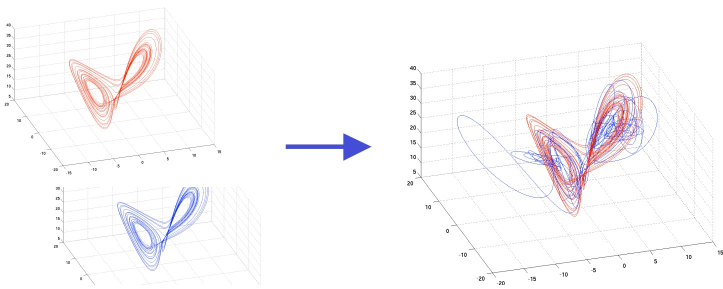
In the problems of interest the dynamical subsystems do not lose their "identity" within the network. Edges in the network (together with the associated coupling coefficients) are responsible for the global phase space topology of a full network. An example of a dynamical network is a spacecraft power system, where sources, sinks and regulators are mutually coupled – many sources provide power to many sinks. In such a system there may be dynamical instabilities – undesired modes of operation where, for example, a power source becomes effectively disconnected from parts of the network. The network structure reacts to the external conditions. In a general self-regulatory system such an event corresponds to the fact that normal operational modes are no longer stable for the given external conditions. Similar ideas apply to the problem of stability in self-sustained habitats composed of multiple coupled dynamical subsystems.

The statistical inference algorithms that we have developed allows us to learn, and track in time, the *structure* of a dynamical network from a set of time-series measurements coming from the individual subsystems (nodes). Our structure-learning algorithm is significantly more efficient then simply learning the full complex dynamical system that includes all the nodes. (The number of model parameters in such a system is a factorial function of the number of nodes.)

We emphasize that the structure of a dynamical network represents a high-level basis for *cause-and-effect* relations in a complex system. The set of such relations can be largely insensitive to the specific numerical values of the coupling coefficients but rather depend on the network structure itself. Additionally, it may be easier to learn the structure than the full dynamical model. Therefore our ability to learn such structure gives us the power to *model* cause-and-effect relations as well as cross-correlations in large set of time-series data coming from a complex dynamical system. Potential failures and undesirable trends in the system operation may reveal themselves in the changes of the network structure. By tracking the structure in time such changes can be detected and mitigated.



Coupling between systems causes significant changes in the behavior. Analysis of the combined system can uncover the couplings

Relevance to Exploration Systems

Long-term space travel and surface operations place demands on space systems that are not currently being met. The long-term reliability and safety of the system must be guaranteed. Currently this is done by including redundancy, and by separating subsystems that should be logically connected. Monitoring of the behavior of the system in a manner that allows diagnosis of incipient failure impacts both the design and operation of the systems. Knowing that faults can be detected and mitigated allows system designers to be less conservative with their designs. On line detection of changes in the system behavior and prognostic of trends allows system maintenance to proceed as required - either by on-line controllers which modify the system to counter the effects of the dynamical instabilities, or by replacement of defective subsystems.

H&RT Program Elements:

This research capability supports the following H&RT program /elements:

ASTP/Software, Intelligent Systems & Modeling

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